

1       **Marker-based estimates of relatedness and inbreeding**  
2       **coefficients: an assessment of current methods**

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7 *Left running head:* J Wang

8 *Right running head:* Concepts and estimators of relatedness and inbreeding

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## 20 Abstract

21 Inbreeding ( $F$ ) of and relatedness ( $r$ ) between individuals are now routinely calculated from marker  
22 data in studies in the fields of quantitative genetics, conservation genetics, forensics, evolution and  
23 ecology. Although definable in terms of either correlation coefficient or probability of identity by  
24 descent (IBD) relative to a reference, they are better interpreted as correlations in marker-based  
25 analyses because the reference in practice is frequently the current sample or population whose  $F$   
26 and  $r$  are being estimated. In such situations, negative estimates have a biological meaning, a  
27 substantial proportion of the estimates are expected to be negative, and the average estimates are  
28 close to zero for  $r$  and equivalent to  $F_{IS}$  for  $F$ . I show that while current  $r$  estimators were developed  
29 from the IBD-based concept of relatedness, some of them conform to the correlation-based concept  
30 of relatedness and some do not. The latter estimators can be modified, however, so that they  
31 estimate  $r$  as a correlation coefficient. I also show that  $F$  and  $r$  estimates can be misleading and  
32 become biased and marker dependent when a sample containing a high proportion of highly inbred  
33 and/or closely related individuals is used as reference. In analyses depending on the comparison  
34 between  $r$  (or  $F$ ) estimates and *a priori* values expected under ideal conditions (e.g. for identifying  
35 genealogical relationship), the estimators should be used with caution.

36

## 37 Introduction

38 Knowledge of the degree of relatedness between individuals due to recent common ancestry is  
39 pivotal in many research areas in quantitative genetics, conservation genetics, forensics, evolution  
40 and ecology (Ritland, 1996; Lynch & Ritland, 1999). For natural populations in which pedigree  
41 records are usually lacking, methods have been proposed (e.g. Lynch, 1988; Queller & Goodnight,  
42 1989; Li *et al.*, 1993; Ritland, 1996; Lynch & Ritland, 1999; Wang, 2002; Thomas, 2010) and  
43 applied to estimating the genetic relatedness between a pair of individuals from their genotypes at  
44 marker loci. These simple estimators, based on allele frequency moments, were shown to provide  
45 unbiased albeit imprecise estimates of relatedness from a typical suit of microsatellite markers when  
46 the assumptions made in developing them were met (e.g. Lynch & Ritland, 1999; Van De Casteele  
47 *et al.*, 2001; Wang, 2002). Several likelihood estimators (Milligan, 2003; Wang, 2007; Anderson &  
48 Weir, 2007) were also proposed to estimate relatedness in more complicated situations involving  
49 inbred or structured populations and imperfect markers suffering from genotyping errors and  
50 mutations. Constraining estimates to their “legitimate” range of  $[0, 1]$ , these likelihood estimators  
51 are biased but can be more precise than moment estimators in certain situations.

52           Relatedness ( $r$ ) and inbreeding ( $F$ ) have by definition an implicit reference population in  
53 which all homologous genes within and between individuals are assumed to be not identical by  
54 descent (IBD). Equivalently, the reference population is assumed to consist of non-inbred and  
55 unrelated individuals. The relatedness between and inbreeding of individuals are thus measured  
56 *relative* to this reference. In a pedigree based analysis in practice, founders who have no known  
57 parents included in the pedigree are assumed non-inbred and unrelated, and thus act effectively as  
58 reference although they may come from different generations. Relatedness between and inbreeding  
59 of any individuals in the pedigree are calculated relative to this reference by path analysis (Wright,  
60 1922) or a recursive tabular method (Emik & Terrill, 1949). If the reference is moved a few  
61 generations backward into the past because the ancestors of some or all of the original founders are  
62 made known and used as founders, then some relatedness between and inbreeding of individuals  
63 will be increased. If the reference is moved a few generations forward because we are only  
64 interested in the most recent coalescences, then some relatedness between and inbreeding of  
65 individuals will be decreased. When we know the differentiation ( $F_{ST}$ ) of the new reference relative  
66 to the old one, we can use it to adjust our estimates of relatedness and inbreeding calculated using  
67 the old reference so that they are relative to the new reference (Powell *et al.*, 2010). However, not  
68 all relatedness and inbreeding coefficients are equally affected by a change of reference, and this  
69  $F_{ST}$  based correction procedure works only as an approximation.

70           In a marker based analysis,  $r$  and  $F$  estimators are also defined and calculated *relative* to an  
71 underlying reference population (Anderson & Weir, 2007; Wang, 2011). In addition to the  
72 assumption of non-inbred and unrelated individuals in the reference, marker based  $r$  and  $F$   
73 estimators assume that the marker allele frequencies in the reference are known. Strictly under these  
74 assumptions, various moment estimators mentioned above are truly unbiased, as checked by  
75 simulations (e.g. Van De Casteele *et al.*, 2001; Wang, 2002) and verified rigorously by analytical  
76 treatments (Wang, 2011). For example, the estimators give an average relatedness of 0.5 and 0.25  
77 for non-inbred diploid full and half siblings respectively, when the allele frequencies used in  
78 simulating the genotypes of unrelated and non-inbred parents of the sampled individuals are  
79 assumed known and used in the estimation. In practice, however, allele frequencies of a population  
80 are rarely known and have to be estimated from a sample of individuals. With few exceptions as  
81 verified by a survey of the literature, a sample of individuals is used first for estimating allele  
82 frequencies assuming  $r=F=0$ , and then for estimating  $r$  and  $F$  using the estimated allele frequencies.  
83 This practice effectively assumes *a priori* non-inbred and unrelated individuals in the sample, which  
84 is used actually as reference. In such a situation, what do  $r$  and  $F$  measure by definition? What are  
85 the marker-based estimators actually estimating?

86 In this study, I will first clarify the definitions of relatedness and inbreeding when a sample  
87 of individuals is used for estimating both allele frequencies and  $F$  and  $r$ . This is important in  
88 understanding what  $F$  and  $r$  really mean, in answering elementary questions such as whether or not  
89 negative  $F$  and  $r$  values make biological sense and whether or not an individual with  $F=-0.1$  is more  
90 inbred than an individual with  $F=-0.2$ . Clarifying the definitions is also important in designing  
91 properly an experiment for  $r$  and  $F$  analysis, in interpreting and applying  $r$  and  $F$  estimates correctly  
92 in downstream analyses, and in developing and comparing rightly different estimators. I will then  
93 investigate, by analytical and simulation analyses, the properties of several  $r$  and  $F$  moment  
94 estimators in the realistic situation of using the current sample or population as reference. I will  
95 modify several  $r$  estimators so that they estimate what are supposed to be estimating in the case of a  
96 sample being used as reference. Hereafter, I focus on the simple  $r$  and  $F$  estimators that are based on  
97 marker allele frequency moments, and the term “estimators” implicitly refer to these moment  
98 estimators except when explicitly preceded by the word “likelihood”.

## 99 **Definitions of $r$ and $F$**

100 The concept of inbreeding coefficient of an individual,  $F$ , was developed by Wright (1921). It was  
101 defined as the correlation between homologous genes of the two gametes (one from father and one  
102 from mother) uniting to form the individual, relative to the total array of such gametes in random  
103 derivatives of the foundation stock (or reference population). Later, Malecot (1948) introduced  
104 another definition of  $F$  as the probability of identity by descent (IBD) of the two homologous genes  
105 at a locus within an individual, where IBD is counted with respect to the reference population in  
106 which all homologous genes are assumed non-IBD. Genes IBD are copies of the same ancestral  
107 allele, and are thus identical in state (IIS) barring the rare events of mutations.

108 In both the correlation and IBD definitions, the  $F$  value of an individual is independent of  
109 locus specific properties such as the mutation rate and the number and frequencies of alleles at a  
110 locus, and is determined solely by the genealogical relationship or the shared ancestry of the  
111 individual’s parents (Wright, 1965). Indeed,  $F$  is traditionally calculated by path analysis (Wright,  
112 1922) of a pedigree without referring to any locus at all. For a given individual, all loci are expected  
113 to have the same  $F$  value because they have experienced the same genealogical process. For the  
114 same reason, different individuals with exactly the same pedigree (e.g. full siblings and twins) are  
115 also expected to have the same  $F$  value at any locus. Therefore, an individual’s  $F$  value calculated  
116 from the pedigree or estimated (learned) from some marker loci can be used to make inference or  
117 explain observations at any loci, taking into account of locus specific properties (like mutations,  
118 selection, mistyping) of the latter loci if necessary.

119 Wright (1965) and others (e.g. Seger, 1981; Grafen, 1985) noted that the correlation and  
120 IBD concepts of  $F$  are identical in some cases, when the reference is a suitable population ancestral  
121 to the current population. They also pointed that, however, the correlation concept is more general  
122 than the IBD concept, and can give meaningful negative values in some situations. For example, the  
123 F1 hybrid individuals from crossing two differentiated parental populations will be expected to have  
124 a negative  $F$ , no matter the reference is the two parental populations combined or the current hybrid  
125 population. In a large population with mixed random selfing and outcrossing, the outbred  
126 individuals will have a negative  $F$  when the current population is used as reference. Similarly, for a  
127 population in which consanguine mating is avoided, individual  $F$  will tend to be negative on  
128 average if the current population is used as reference. These negative  $F$  values make biological  
129 sense, signifying that the probability of the two homologous genes within an individual being IBD  
130 is smaller than that of two homologous genes drawn at random from the reference population. In  
131 contrast, the IBD concept will never give a negative  $F$ , because it is a probability.

132 In principle, the correlation concept puts no constraint on which population can be used as a  
133 reference. One can use an ancestral, the current (focal), and even a descendant population as a  
134 reference, yielding in general a decreasing  $F$  value for a given individual. Pedigree analyses  
135 invariably use an ancestral population as reference, while marker analyses frequently use the current  
136 population from which a sample of individuals is taken for  $F$  analysis as the actual reference. There  
137 is neither methodological nor conceptual difficulty in using a descendant population as the  
138 reference in a marker-based analysis. In contrast, the IBD based  $F$  has to use an ancestral population  
139 as reference, because by definition negative values are prohibited and have no meaning. If the  
140 current or a descendent population were used as reference, the  $F$  of most or all individuals would be  
141 invariably zero.

142 The necessary but ambiguous and arbitrary nature of a reference in both the correlation and  
143 IBD concepts of  $F$  dictates that  $F$  values are always relative to an implicit reference population  
144 assumed to be composed of non-inbred and unrelated individuals such that all homologous genes in  
145 the reference are non-IBD. For any given individual,  $F$  can virtually take any value in the legitimate  
146 range  $[-1, 1]$  as a correlation coefficient, or in the range  $[0, 1]$  as an IBD coefficient, depending on  
147 the reference one chooses to measure  $F$  against. This relativity leads to the claims that  $F$  has  
148 something arbitrary in its definition (Maynard Smith, 1998, p141), to the so-called ‘inbreeding  
149 paradox’ (Seger, 1981), and the suggestion that relatedness (and  $F$  as well) is a measure of our  
150 information and not of anything real (Jacquard, 1974, p171). These claims are true to some extent,  
151 but they do not nullify the usefulness of  $F$  in population genetics theory and applications. So long as  
152 the reference is not extremely far away from the current population such that mutations and

153 selections become non-negligible compared with the genealogical process (inbreeding and drift),  
154 the  $F$  values suffice in most analyses such as regression and correlation analyses involving  $F$  as a  
155 variable. In these analyses, it is the relative  $F$  values of different individuals that matter and a linear  
156 transformation of  $F$  values does not alter the regression or correlation analysis result. For pedigree  
157 based analyses, however, a pedigree that is too deep or too shallow (i.e. the reference is too far  
158 away from and too close to the current population, respectively) will lead to  $F$  values close to 1 or 0,  
159 respectively, for all current individuals. Consequently, the variance of  $F$  would become much  
160 smaller than the maximum obtainable from a pedigree with an appropriate depth, resulting in under-  
161 or over-estimation of inbreeding effects in regression or correlation analyses. In contrast, marker  
162 based analyses are affected only when the reference is too far away into the past, and are little  
163 affected when the reference is or is close to the current population.

164         There are other definitions of  $F$  in the literature. Rousset (2002) noted the limitations of  
165 IBD-based concept of inbreeding, and gave a generic definition of  $F$  as ratios of differences of  
166 probabilities of genes identical in state (IIS). In ideal situations (e.g. the absence of locus specifics  
167 like mutations), it is equivalent to Wright's correlation definition when applied to markers.  
168 However, several difficulties arise with this IIS based definition. First, gene identities and thus IIS  
169 are more or less arbitrary. For example, classical genetics recognizes three alleles, A, B, and O that  
170 determine the compatibility of blood transfusions at the gene locus for the ABO blood type  
171 carbohydrate antigens in humans. It is now recognized that each of the three alleles is actually a  
172 class of multiple alleles having different DNA sequences and coding for different proteins with  
173 identical properties. More than 70 alleles are now identified at the ABO locus (Yip, 2002). A  
174 homozygote in the old 3-allele system may well be a heterozygote in the new +70-allele system,  
175 causing a huge drop in homozygosity or probability of IIS in an individual or a population. In  
176 contrast,  $F$  defined as correlation or IBD probability due to shared ancestry is unaffected by how  
177 alleles and loci are defined, and by the polymorphisms of markers. Second, the definition is not  
178 applicable to pedigree analysis. The IBD and correlation definitions of  $F$  are broad and coherent,  
179 and apply to both pedigree and marker analyses. Using the founders of a pedigree as reference,  
180 pedigree and markers should yield the same expected value of  $F$  for a given individual. These  
181 definitions make it possible to develop likelihood or Bayesian methods to use pedigree and marker  
182 data jointly in inferring realised (rather than expected)  $F$  and relatedness, and in estimating marker  
183 genotypes and allele frequencies from incomplete pedigree and marker information (e.g. Boehnke,  
184 1991; Wang & Santure, 2009). Third, IIS based  $F$  depends not only on genealogy, but also on locus  
185 specifics. As a result, the expected  $F$  value of a given individual varies across loci, depending on  
186 locus specific properties like mutation rate and mistyping rate. In general, effects of mutations can

187 be negligibly small (Rousset, 2002), because in practice the time scale for  $F$  is usually much smaller  
188 than  $1/u$  where  $u$  is the mutation rate. However, other locus properties may have a substantial effect  
189 on IIS and thus on  $F$ . In the imperfect world, genotyping errors are a rule rather than an exception  
190 (Bonin *et al.*, 2004). Allelic dropouts and null alleles are particular common for microsatellite  
191 markers, and could cause an apparent increase in IIS and thus IIS-based  $F$ . It is true such mistypings  
192 can affect marker-based estimates of  $F$  in any concepts. However, under the correlation or IBD  
193 definition,  $F$  has the same expected value across loci such that a method can be developed to  
194 account for mistypings if the model and rate of their occurrences are known (e.g. Wang, 2007).

195 Closely related to  $F$  is the concept of coancestry coefficient or the coefficient of kinship,  $\theta$ ,  
196 between two individuals. In Wright's correlation definition,  $\theta$  between two individuals is simply  
197 equal to the expected  $F$  of their (hypothetical) offspring, and  $F$  can be regarded as the coancestry  
198 coefficient between the male and female gametes that unite to form an individual. In terms of IBD,  
199  $\theta$  is the probability that two homologous genes, one taken at random from each individual, are  
200 identical by descent. Relatedness,  $r$ , is simply  $r=2\theta$  if both individuals are non-inbred (Lynch &  
201 Ritland, 1999).

202 It is noticeable that most marker based  $r$  estimators are developed based on the IBD concept  
203 (e.g. Lynch, 1988; Li *et al.*, 1993; Ritland, 1996; Lynch & Ritland, 1999; Wang, 2002; Thomas,  
204 2010; Milligan, 2003; Wang, 2007; Anderson & Weir, 2007), using the full set or a subset of the 9  
205 condensed IBD states for the 4 (2 in each individual) homologous genes and their probabilities  
206 (Harris, 1964; Jacquard, 1972). These estimators implicitly assume an appropriate ancestral  
207 population as the reference, and allele frequencies from the reference are known and are used in  
208 calculating the estimators. When these assumptions are met, these estimators are unbiased as  
209 checked by both simulations (e.g. Lynch & Ritland, 1999; Wang, 2002) and rigorous analytical  
210 treatments (Anderson & Weir, 2007; Wang, 2011). Negative values from the estimators are taken as  
211 due to sampling errors (e.g. Lynch & Ritland, 1999). In a similar vein, likelihood estimators  
212 (Milligan, 2003; Wang, 2007; Anderson & Weir, 2007) of  $r$  are constrained in the "legitimate"  
213 range of [0,1] based on the IBD concept, and as a result are upwardly biased when the assumptions  
214 are violated.

215 In practical applications, however,  $r$  and  $F$  are frequently estimated using allele frequencies  
216 calculated from the current sample of individuals whose  $F$  and  $r$  are being estimated. This practice  
217 effectively uses the current population (or sample) as the reference. A shift of reference from an  
218 ancestral population assumed in developing the estimators to the current population (from which the  
219 individuals are sampled) or sample assumed in applying the estimators alters imperceptibly and



insidiously the meanings of  $r$  and  $F$ . The estimates thus obtained can no longer be interpreted as probabilities of IBD of homologous genes between and within individuals relative to the reference, as is in developing the estimators. Rather, they should be understood as correlations of homologous genes between and within individuals (Hardy & Vekemans, 1999; Powell *et al.*, 2010) due to shared ancestry, as Wright (1921) originally conceived. The shift in reference to the current sample causes some  $F$  values of and some  $r$  values between individuals to be legitimately negative, and so they obviously cannot be interpreted as probabilities and should not be simply dismissed as due to sampling errors. They can be understood, however, as the correlation of homologous alleles within and between individuals. The negative values imply that homologous genes within and between individuals are IIS at a lower probability than the average, because the shared ancestors are more distant or/and fewer than the average.

Using the current sample as reference,  $r$  (or  $F$ ) signifies the expected relative excess (when positive) or deficit (when negative) of the occurrences of homologous genes that are IIS between (or within) individuals due to the relative excess or deficit of shared ancestry. The mean estimate of  $r$  among pairs of individuals in a sample should be close to zero, because the probability of IBD of homologous genes between individuals is on average close to that of homologous genes taken at random from the sample except when it is extremely small. The mean estimate of  $F$  among individuals in a sample should be equivalent to Wright's  $F_{IS}$  by definition. Given the frequency of an allele,  $p$ , at a locus in the sample, an individual  $i$  with inbreeding coefficient  $F_i$  will be homozygous for the allele at a probability of  $pF_i + p^2(1 - F_i)$ . This probability is smaller than, equal to, and larger than the mean,  $p^2$ , when the individual has a negative, zero, and positive  $F_i$ , respectively. This interpretation of  $F$  is true across loci. For example, the probability of a multilocus homozygote for individual  $i$  is  $\prod_{l=1}^L (p_l F_i + p_l^2(1 - F_i))$ , where  $p_l$  is frequency of the allele at locus  $l$  ( $=1, \dots, L$ ) that is homozygous for the individual. This interpretation of  $F$  is also true among individuals. For example, the frequency of a homozygote for an allele of frequency  $p$  in the sample is  $\frac{1}{n} (\sum_{i=1}^n (pF_i + p^2(1 - F_i)))$ , which reduces to  $p^2$  because the average of  $F_i$  is zero in the sample of  $n$  individuals. Relatedness has a similar explanation.

## **Estimators of $r$ and $F$**

As shown above,  $r$  (or  $F$ ) should be interpreted as correlations and should have an expected value that is equal or close to 0 (or  $F_{IS}$ ) irrespective of the genealogy of the sample, when the current population or sample is actually used as the reference. Is this true with the estimators used currently in practical applications? Below I show by analytical and simulation approaches that while some  $r$  estimators can be construed as correlation coefficient, others are not. In the latter case, however, the

estimators can be modified so that they estimate  $r$  as a correlation coefficient. In contrast, all current estimators of  $F$  can be interpreted as correlation coefficient.

I assume a single marker locus with  $k$  ( $>1$ ) codominant alleles,  $A_i$  ( $i=1\sim k$ ), is used in estimating the  $r$  and  $F$  of a large sample of individuals taken from a half-sib family (The same results are obtained from a full-sib family, and the derivations are available upon request). All individuals in the sample share the same non-inbred parent of one sex but have distinctive non-inbred and unrelated parents of the other sex. Both  $r$  and  $F$  can be defined and estimated using either parental or current population as reference. In the former case, individuals in the reference are non-inbred and unrelated, and the frequency of allele  $A_i$ ,  $\hat{p}_i$ , used in calculating  $r$  and  $F$  is the parental allele frequency  $p_i$  assumed known without error. In the latter case, individuals in the reference are non-inbred half siblings, and  $\hat{p}_i$  used in calculating  $r$  and  $F$  is estimated using the genotypes of sampled individuals under the assumption of non-inbred and unrelatedness.

### ***Relatedness estimators***

By the IBD or correlation definition using the parental population as reference, we have an expected value of  $r=0.25$  for each pair of individuals, and  $\bar{r}=0.25$  across pairs. By the correlation definition using the current population (sample) as reference, we have an expected value of  $r=0$  for each pair of individuals, and  $\bar{r}=0$  across pairs. In the following, I investigate whether  $\bar{r}=0$  is obtained from each of a number of estimators when the current population is used as reference.

*Estimator by Queller and Goodnight (1989)*: There are a number of variants to this widely applied estimator (denoted as QG), and I choose to use the symmetric one obtained by averaging the estimates using each of the two individuals as reference. For individuals X and Y with genotypes  $\{a,b\}$  and  $\{c,d\}$ , respectively, at a locus (note that alleles  $A_i$  for  $i=1\sim k$  are denoted by  $a, b, c, d$  to avoid subscripts), the estimator is

$$\hat{r} = (\hat{r}_{XY} + \hat{r}_{YX})/2, \quad (1)$$

where estimates using individual X and Y as references are

$$\hat{r}_{YX} = \hat{r}[c, d|a, b] = \frac{\delta_{ac} + \delta_{ad} + \delta_{bc} + \delta_{bd} - 2(p_a + p_b)}{2(1 + \delta_{ab} - p_a - p_b)}, \quad (2)$$

$$\hat{r}_{XY} = \hat{r}[a, b|c, d] = \frac{\delta_{ac} + \delta_{ad} + \delta_{bc} + \delta_{bd} - 2(p_c + p_d)}{2(1 + \delta_{cd} - p_c - p_d)}, \quad (3)$$

respectively, and the Kronecker delta variable  $\delta_{ij}=1$  if  $i=j$  and  $\delta_{ij}=0$  otherwise. In some special cases, equations (1-3) are undefined. For a monomorphic marker ( $k=1$ ) or a biallelic marker ( $k=2$ )

with both X and Y being heterozygous, both (2) and (3) are undefined and as a results (1) is also undefined. In such a case,  $\hat{r}$  is taken more or less arbitrarily as zero. When X and Y are a heterozygote and homozygote, respectively, at a biallelic locus, (2) is undefined and the estimator becomes  $\hat{r} = \hat{r}_{XY}$ . Similarly  $\hat{r} = \hat{r}_{YX}$  when Y and X are a heterozygote and homozygote at a biallelic locus, respectively.

Under random mating, the genotypes of half siblings in the sample depend on the genotype of the shared parent,  $G_s$ , and allele frequencies of the parental population.  $G_s$  can be either a homozygote,  $\{a,a\}$ , or a heterozygote,  $\{a,b\}$  ( $a \neq b$ ). In the former case, the sibling genotypes are  $\{a,x\}$ , where  $x=a, b, \dots$ , with a probability of  $p_x$ . The allele frequency calculated from the sample assuming outbred and unrelated individuals is  $\hat{p}_x = (\delta_{ax} + p_x)/2$ , where  $\delta_{ax} = 1$  if  $x = a$  and  $\delta_{ax} = 0$  otherwise. Given  $G_s = \{a,a\}$ , the average relatedness between individuals of the sample is  $\bar{r} = \sum_{b=1}^k \sum_{d=1}^k p_b p_d (\hat{r}[a,b|a,d] + \hat{r}[a,d|a,b])/2$ . Substituting  $\hat{r}$  by (2-3) and using sample allele frequencies  $\hat{p}_x$  in place of  $p_x$  in the estimator, I obtain  $\bar{r} \equiv 0$  for  $k > 2$ , and  $\bar{r} \equiv -p_a^2$  for  $k=2$ .

Similarly, when the shared parent has a heterozygous genotype  $G_s = \{a,b\}$  ( $a \neq b$ ), the offspring genotypes, their frequencies, and the sample allele frequencies are listed in Table 1. Following the approach above, I obtain  $\bar{r} \equiv 0$  for  $k > 2$ , and  $\bar{r} \equiv (12p_1p_2 - 3)/(4p_1p_2 + 3)$  for  $k=2$ , when allele frequencies calculated from the sample assuming unrelated and non-inbred individuals are used in the estimation.

In summary, when the current population (sample) is used as reference (i.e. the allele frequencies estimated from the sample are used in  $r$  estimation), the average  $r$  between half siblings is zero, except when  $k=2$ . For a biallelic locus ( $k=2$ ),  $\bar{r} = 0$  only in the special case of a heterozygote of the shared parent and equal allele frequencies (i.e.  $p_1=p_2=0.5$ ); otherwise,  $\bar{r} < 0$ . The negative  $\bar{r}$  when  $k=2$  occurs because the estimator is undefined with a heterozygous reference individual, and is set, more or less arbitrarily, a value of 0.

*Estimator by Ritland (1996):* This estimator (denoted as R), derived by Li & Horvitz (1953) and Ritland (1996), is

$$\hat{r} = \frac{2}{k-1} \left[ \left( \sum_{i=1}^k \frac{S_i}{p_i} \right) - 1 \right], \quad (4)$$

where  $S_i$  gives the similarity for allele  $i$  between individuals X and Y.  $S_i$  has 4 possible values, which are 0, 0.25 and 1 when both X and Y have exactly 0, 1 and 2  $i$  alleles, and 0.5 when X and Y have a total of 3  $i$  alleles.

312 Using the genotype and estimated allele frequencies of half sib families listed in Table 1, the  
 313 estimator always gives an average relatedness of 0, irrespective of the genotype of the shared parent  
 314 and the number and frequencies of alleles at a locus.

315 *Estimator by Lynch and Ritland (1999)*: The estimator (denoted as LR) of relatedness between  
 316 individuals X and Y with genotypes {a,b} and {c,d} respectively is given by (1), where the  
 317 estimates using X and Y as references are

$$318 \quad \hat{r}_{YX} = \hat{r}[c, d|a, b] = \frac{p_a(\delta_{bc} + \delta_{bd}) + p_b(\delta_{ac} + \delta_{ad}) - 4p_a p_b}{(1 + \delta_{ab})(p_a + p_b) - 4p_a p_b}, \quad (5)$$

$$319 \quad \hat{r}_{XY} = \hat{r}[a, b|c, d] = \frac{p_c(\delta_{da} + \delta_{db}) + p_d(\delta_{ca} + \delta_{cb}) - 4p_c p_d}{(1 + \delta_{cd})(p_c + p_d) - 4p_c p_d}, \quad (6)$$

320 respectively. Applying the estimator to a large half sib family as listed in Table 1 yields an average  
 321 relatedness of 0, irrespective of the genotype of the shared parent, except for the special case of a  
 322 biallelic locus with equal allele frequencies. In this special case, the LR estimator becomes  
 323 undefined when the reference individual is a heterozygote (Lynch & Ritland, 1999).

324 *Estimator by Lynch (1988) and Li et al. (1993)*: This estimator (denoted as LL), proposed by Lynch  
 325 (1988) and improved by Li et al. (1993), estimates  $r$  using a similarity index  $S_{XY}$ . This index is  
 326 defined as the average fraction of alleles at a locus in a reference individual, X or Y, for which there  
 327 is another allele in the other individual, Y or X, that is IIS. Thus,  $S_{XY}$  has a value of 1 for genotype  
 328 pairs  $\{A_i A_i, A_i A_i\}$  or  $\{A_i A_j, A_i A_j\}$ , 0.75 for  $\{A_i A_i, A_i A_j\}$ , 0.5 for  $\{A_i A_j, A_i A_k\}$ , and 0 for  $\{A_i A_j,$   
 329  $A_k A_l\}$ , where different subscripts  $i, j, k, l$  indicate distinctive alleles. The estimator for individuals X  
 330 and Y is

$$331 \quad \hat{r} = \frac{S_{XY} - S_0}{1 - S_0}, \quad (7)$$

332 where  $S_0 = 2a_2 - a_3$  (with  $a_m = \sum_{i=1}^n p_i^m$  for  $m = 2, 3$ ) is the expected similarity index for unrelated  
 333 individuals.

334 Applying the estimator to a large half-sib family (Table 1), I obtain, after tedious algebra, an  
 335 average relatedness  $\bar{r}[i, i] = \frac{1 - p_i - p_i^2 + a_3}{5 - 5p_i + 3p_i^2 - 4a_2 + a_3}$  and  $\bar{r}[i, j] = \frac{1 - (p_i + p_j) - 2(p_i^2 + p_j^2) + 4a_3}{25 - 13(p_i + p_j) + 6(p_i^2 + p_j^2) - 16a_2 + 4a_3}$  when  
 336 the shared parent has a homozygote genotype  $\{A_i, A_i\}$  and a heterozygote genotype  $\{A_i, A_j\}$   
 337 ( $j \neq i = 1 \sim k$ ), respectively. It can be shown that  $\bar{r} > 0$  in both cases, and the magnitude depends on the  
 338 number and frequencies of alleles. This means that LL estimator does not estimate  $r$  as a correlation

coefficient when the current sample (population) is used as reference. Otherwise, the expected  $r$  should be zero, like the QG, R, and LR estimators.

To understand how much the LL estimator deviates from the expected value of  $\bar{r} = 0$  if it were a correlation estimator, let's consider the simple case of a biallelic locus. Combining the three possible genotypes of the shared parent, I obtain an overall average relatedness of  $\bar{r} = \sum_{i=1}^2 p_i^2 \bar{r}[i, i] + 2p_1 p_2 \bar{r}[1, 2]$ , which simplifies to  $\bar{r} = \frac{p_1 p_2 (7 - 4p_1 p_2)}{(1 + p_1)(1 + p_2)(1 + 2p_1)(1 + 2p_2)}$ . Figure 1 plots  $\bar{r}$  as a function of allele frequency  $p_1$  ( $=1-p_2$ ), and shows simulation values for comparison. As expected, simulation and analytical values agree very well. Except when allele frequency is close to zero or one such that the marker gives little information,  $\bar{r}$  is substantially higher than 0. The maximal value of  $\bar{r}$  is  $1/6$  when  $p_1 = p_2 = 0.5$ . It is clear that the LL estimator applies to the IBD definition of relatedness only, and becomes meaningless when the current sample contains a high proportion of related individuals and is used as the reference because in such a case the estimates depend heavily on allele frequencies. It also implies that LL relatedness estimates for pairs of individuals are incomparable if these individuals have missing data at different loci.

It is possible to modify LL estimator so that, like QG, LR and R estimators, it applies to the more general definition of relatedness in terms of correlation (Wright, 1921). The original LL estimator is calculated using a constant  $S_0$ , which is the *expected* similarity for unrelated individuals. For a reference population (such as an appropriate ancestral population) of non-inbred and unrelated individuals,  $S_0$  can be calculated as  $S_0 = 2a_2 - a_3$  from allele frequencies. For a more general reference that may contain related and inbred individuals,  $S_0$  should be replaced by the average *observed* similarity over all possible pairs of individuals,  $S_a$ . When the reference is a large random mating ancestral population as assumed in deriving the LL estimator, we have  $S_a = \sum_{a=1}^k \sum_{b=1}^k \sum_{c=1}^k \sum_{d=1}^k p_a p_b p_c p_d S_{(a,b),(c,d)}$  at a locus with  $k$  codominant alleles, where  $S_{(a,b),(c,d)}$  is the same as  $S_{XY}$  in (7) and denotes the similarity index for a genotype {a,b} and a genotype {c,d}. It can be shown, after some algebra, that  $S_a$  reduces to  $S_0 = 2a_2 - a_3$  as expected. When the reference is the current sample of  $n$  individuals being calculated for relatedness, then

$$S_a = \frac{2}{n(n-1)} \sum_{i=1}^n \sum_{j=i+1}^n S_{ij}, \quad (8)$$

where  $S_{ij}$  is defined similarly to  $S_{XY}$  in (7).

Replacing  $S_0$  by  $S_a$ , (7) gives relatedness estimates relative to a reference chosen by a researcher. When the reference is an ancestral, the current, and a descendent population, the average

relatedness across pairs of individuals in a sample tends to be greater than, equal to, and smaller than zero respectively, independent of markers and their allele frequencies.

Consider the half sib family listed in Table 1 as an example. When the shared parent has a homozygote genotype  $\{A_i, A_i\}$  at a locus with  $k$  alleles, the half siblings have an average observed similarity index  $S_a = \sum_{j=1}^k \sum_{l=1}^k p_j p_l (1 + \delta_{jl})/2$  which, after some algebra, reduces to  $S_a = (1 + a_2)/2$ . The average relatedness is  $\bar{r} = \sum_{j=1}^k \sum_{l=1}^k p_j p_l \left( \frac{1 + \delta_{jl}}{2} - S_a \right) / (1 - S_a)$ , which reduces to  $\bar{r} \equiv 0$ . It can be shown similarly that  $\bar{r} \equiv 0$  when the shared parent has a heterozygote genotype  $\{A_i, A_j\}$  ( $j \neq i$ ).

*Estimator by Wang (2002)*: This estimator (denoted by W) uses the similarity index of Lynch (1988) and Li *et al.* (1993) but can estimate both two- and four-gene relatedness, and thus the total relatedness  $r$ . Using the same similarity index as LL estimator, W estimator is similar to LL estimator and applies to the IBD definition of relatedness only. When the current sample is used as reference, W estimator gives an average relatedness larger than 0 when relatives are included in the sample. However, unlike LL estimator, W estimator is complicated and it is difficult to derive its  $\bar{r}$  even for the simple case of a sample of individuals having the same relationship, such as a half siblings. Simulations showed that W estimator has a  $\bar{r}$  similar to LL estimator, as shown in Figure 1 for a biallelic locus.

To modify W estimator such that it is relative to a reference no matter the reference is an ancestral or current population (sample), I transform the original 2- or 4-gene relatedness or total relatedness estimates,  $w$ , from W estimator to  $(w - \bar{w})/(1 - \bar{w})$ , where  $\bar{w}$  is the average of the original estimates across all dyads.

### ***Inbreeding estimators***

In the IBD or correlation definition using the parental population as reference, we have an expected value of  $F=0$  for each individual in the sample and thus  $\bar{F}=0$ . In the correlation definition using the current population (sample) as reference, we have an expected value of  $F<0$  for each individual and thus  $\bar{F}<0$  because the two homologous genes within an individual have a lower IBD probability than two genes taken at random from the sample (i.e. individuals are more heterozygous than expected at Hardy-Weinberg equilibrium,  $F_{IS}<0$ ).

A number of estimators (Li & Horvitz, 1953; Ritland, 1996; Wang, 2011) have been developed to estimate  $F$  from marker data. Herein I choose to analyze a few. I show that these estimators estimate  $F$  as a correlation coefficient (Wright, 1921), and the average  $F$  among

individuals is expected to be smaller than zero when the current sample (population) containing highly related individuals is used as reference. However, these estimators may give misleading results in such a case because the estimates become dependent on allele frequencies of the markers.

*Estimator by Li & Horvitz (1953) and Ritland (1996)*: This estimator (denoted as LHR) was derived based on the proportion of alleles in homozygous condition at a single locus,  $\sum_{i=1}^k \frac{z_{ii}}{p_i} = 1 + F(k - 1)$ , where  $z_{ii} = (1 - F)p_i^2 + Fp_i$  is the proportion of homozygotes for allele  $A_i$  and  $p_i$  is the frequency of allele  $A_i$ . In the expression for  $z_{ii}$ ,  $F$  can be interpreted as correlation and can take a negative value for an individual having less homozygosity than an individual expected in the reference population under Hardy-Weinberg equilibrium. Solving for  $F$  gives an estimator

$$F = \frac{1}{k-1} \sum_{i=1}^k \frac{S_i - p_i^2}{p_i}, \quad (9)$$

where  $S_i = 1$  if the individual is homozygous for allele  $i$  and  $S_i = 0$  if otherwise. For the half sib family considered in Table 1, all individuals have an expected  $F=0$  because their parents are unrelated. Estimator (9) gives indeed  $F=0$  when the allele frequencies of the parental population are known without error and are used in the estimation. For a shared parent with a homozygous  $\{A_i, A_i\}$  and heterozygous  $\{A_i, A_j\}$  genotype, the averages of individual  $F$  values calculated by (9) are  $\frac{-1}{k-1}(1 - p_i) + \frac{\frac{1}{p_i}-1}{k-1}(p_i)$  and  $\frac{-1}{k-1}\left(1 - \frac{p_i}{2} - \frac{p_j}{2}\right) + \frac{\frac{1}{p_i}-1}{k-1}\left(\frac{p_i}{2}\right) + \frac{\frac{1}{p_j}-1}{k-1}\left(\frac{p_j}{2}\right)$ , respectively. Both reduce to zero as expected, regardless of the number and frequencies of alleles at a locus.

However, when the observed allele frequencies in the sample are used in the estimation, (9) gives  $F = \frac{-(1-p_i)}{(k-1)(1+p_i)}$  and  $F = \frac{-(1-4p_i p_j)}{(k-1)(1+2p_i)(1+2p_j)}$  when the shared parent is a homozygote  $\{A_i, A_i\}$  and heterozygote  $\{A_i, A_j\}$ , respectively. In both cases  $F < 0$  in general, and  $F = 0$  only when the shared parent has a heterozygous genotype at a biallelic locus with equal allele frequencies. Figure 2 plots the average  $F$  when the shared parent has a homozygous and heterozygous genotype, and has the two kinds of genotypes at frequencies under Hardy-Weinberg equilibrium. As is clear,  $F$  is negative in general, and its magnitude depends on parental allele frequencies. This means different markers with different numbers and frequencies of alleles will yield different expected  $F$  estimates. This negative and marker-dependent  $F$  is caused by using allele frequencies calculated from the current sample which is assumed to contain unrelated individuals.

*Estimator by Li & Horvitz (1953) and Carothers et al. (2006)*: This estimator (denoted as LHC), based on the consideration of expected heterozygosity  $h$ , is

$$\hat{F} = \frac{h-1+S}{h}, \quad (10)$$

where  $S = 1$  if the individual is a homozygote and  $S = 0$  if otherwise. Similar to (9), (10) is an unbiased estimator of  $F$  as a correlation coefficient when individuals in the reference population are non-inbred and unrelated (Carothers *et al.*, 2006). If some individuals in the reference are related, however, the expected value of (10) is greater and smaller than zero when the actual inbreeding is higher and lower than average relatedness in the reference, respectively. With a significant level of relatedness among individuals in the reference, (10) becomes marker dependent and does not reflect purely the level of inbreeding.

Consider the half sib case of Table 1 and use the current population (sample) as reference. When the shared parent is a homozygote,  $\{A_i, A_i\}$ , and heterozygote,  $\{A_i, A_j\}$ , the expected heterozygosity of the sample can be obtained from Table 1 as  $h = (3 - 2p_i - a_2)/4$  and  $h = (7 - 2p_i - 2p_j - 2a_2)/8$ , respectively. Using these and (10), I obtain the average  $F$  of the sample

$$\bar{F} = -\sum_{i=1}^k \frac{p_i^2(1+a_2-2p_i)}{3-a_2-2p_i} - \sum_{i=1}^k \sum_{j=i+1}^k \frac{2p_i p_j(1+2a_2-2p_i-2p_j)}{7-2a_2-2p_i-2p_j}.$$

For a biallelic locus, this is identical to the average  $F$  from estimator (9). For a locus with  $k$  equifrequent alleles, the average  $F$  values calculated by (10) and (9) are plotted as a function of  $k$  in Figure 3. As can be seen, both estimators are negative and marker-dependent when the current sample containing related individuals is used as reference.

### The magnitude of $r$ and $F$ values

The above analytical treatment considered a sample containing a single large family, and all sampled individuals have the same expected inbreeding and relatedness. When a sample containing individuals of variable relatedness and inbreeding coefficients is used as reference, the magnitude of  $r$  and  $F$  estimates should be taken with caution, because they are not determined purely by the actual relatedness between and inbreeding of individuals involved, but also dependent on the actual relatedness and inbreeding of other individuals in the sample, and may also be affected by the allele frequencies of markers.

Let's consider a simple example. Suppose a sample containing  $N$  individuals taken at random from  $n$  half-sib families in a population, with each family contributing  $m=N/n$  (integer) half siblings who share the same father but have distinctive mothers. All parents of the half sib families are non-inbred and unrelated. When the current sample is used as reference (i.e. its allele frequencies are calculated assuming  $F=r=0$  and used in the estimation), the average estimated



relatedness  $q\bar{r}_{hs} + (1 - q)\bar{r}_{ns} = 0$ , where  $q = \frac{nm(m-1)/2}{N(N-1)/2}$  is the proportion of half-sib dyads and  $\bar{r}_{hs}$  and  $\bar{r}_{ns}$  are the average relatedness for half-sib and non-sib dyads, respectively.  $\bar{r}_{hs}$  and  $\bar{r}_{ns}$  are smaller than 0.25 and 0 respectively, the expected values when the parental population is used as reference or when the reference does not contain related and inbred individuals. The values of  $\bar{r}_{hs}$  and  $\bar{r}_{ns}$  depend on the genetic structure of the sample ( $n$  and  $m$ ), and the estimator and markers used.

Simulations were conducted to check the above analytical predictions. I fixed  $m$  at 50, and varied  $n$  between 2 and 10. Ten markers, each having  $k=3\sim 10$  alleles in a triangular frequency distribution of  $p_i = i/(2k(k+1))$  in the parental population were simulated. Allele frequencies at each locus were calculated from the sample assuming unrelated non-inbred individuals and were used in calculating the LR, R, and QG estimators. Values of  $\bar{r}_{hs}$  and  $\bar{r}_{ns}$  across 100 replicate runs are shown in Figure 4. As can be seen, with an increase in  $n$ ,  $\bar{r}_{hs}$  and  $\bar{r}_{ns}$  for each estimator increase towards to the expected values of 0.25 and 0 when the reference contains no related individuals. Different estimators give different values of  $\bar{r}_{hs}$  and  $\bar{r}_{ns}$ , the difference being large between QG and the other estimators.  $\bar{r}_{hs}$  and  $\bar{r}_{ns}$  are also marker dependent. Markers with a higher polymorphism tend to give higher values of  $\bar{r}_{hs}$  and lower values of  $\bar{r}_{ns}$ , especially for R and LR estimators. The estimate of average relatedness across all possible pairs of individuals (data not shown) is very close to zero, regardless of the estimators, the family structure of the sample, and the markers.

## Discussions

Although marker based relatedness estimators are developed using the IBD concept of relatedness, they are better interpreted in terms of Wright's (1921) original correlation concept of relatedness. This is because the IBD definition has to use an appropriate ancestral population as the reference, and assume non-inbred and unrelated individuals in the reference. In practice, this definition poses no problem when a pedigree of sufficient depth is analysed for relatedness. However, when marker data are analysed for relatedness, frequently genotype or allele frequency data are unavailable from an ancestral population, and allele frequencies used in calculating relatedness have to be estimated from the current sample in which relatedness between individuals is being calculated. This practice effectively uses the current population (sample) as reference, and an estimator conforming to the correlation concept of relatedness should give an average estimate of zero. This is true regardless of the actual relatedness among individuals in the sample, as shown by simulation and analytical results in this study. Relatedness between two individuals can be understood as the probability of IBD between two genes, one taken at random from each individual, relative to the probability of IBD between two genes taken at random from the reference population. A negative value signifies

491 that the individuals are less related in ancestry than the average, and as a result have genotypes less  
492 similar in expectation than the average.

493 The shift of reference from an ancestral to the current population also entails that the  
494 constraint of IBD coefficients in the range of  $[0,1]$  used by likelihood estimators of  $r$  (Milligan,  
495 2003; Wang, 2007; Anderson & Weir, 2007) is not justified, and may lead to biased  $r$  estimates.  
496 This bias is caused by the presence of related or/and inbred individuals in a sample which are  
497 assumed absent in calculating allele frequencies, and persists even if genomic data with millions of  
498 SNPs are used. For a sample taken at random from a large outbred population, most individuals will  
499 be unrelated or only loosely related (Csillery *et al.*, 2006), and the bias of likelihood estimators  
500 should be small and could be negligible compared with the typically large sampling variance of  $r$ .  
501 For small or inbreeding (e.g. partial selfing) populations, however, the bias can be substantial. In  
502 general, the higher the variance in actual relatedness and/or inbreeding in a sample, the higher the  
503 bias will the likelihood estimators yield. Operationally it is simple to extend the legitimate range of  
504  $r$  to  $[-1,1]$  in searching for the maximum likelihood estimate of  $r$  (Konovalov & Heg, 2008), and  
505 such a procedure will undoubtedly reduce estimation bias. However, it is unclear how to determine  
506 the exact range of values for each of the 9 IBD coefficients for a pair of possibly inbred individuals,  
507 and how to ensure  $r$  estimates are constrained in the range  $[-1,1]$  as a result. More work is needed in  
508 this direction.

509 The present study shows that the practice of using the current sample as reference causes  
510 two difficulties in the estimation and interpretation of  $r$ . The first difficulty is that  $r$  should be  
511 defined and interpreted as correlation as conceived originally by Wright (1921), rather than a  
512 probability of IBD as currently widely perceived. As correlation, the average  $r$  across pairs of  
513 individuals in the entire sample is always close to zero, and negative  $r$  values have biological  
514 meanings. Accordingly,  $r$  estimators should be estimating  $r$  as a correlation coefficient rather than a  
515 probability of IBD. I showed that indeed some estimators (e.g. QG, LR and R) can be interpreted as  
516 such, while others using similarity index (e.g. LL and W) cannot. The latter estimators, however,  
517 can be modified to conform to the correlation definition of relatedness. The second difficulty comes  
518 from the assumption of unrelated individuals in the current sample (inbreeding has negligible effect  
519 compared with relatedness because it is the latter that predominantly determines the probability of  
520 IBD of genes taken at random from the sample), which is necessary for estimating allele  
521 frequencies. The use of the same sample for estimating relatedness and allele frequencies introduces  
522 circularity, and violates the basic assumption of independence of  $r$  and allele frequencies in all  
523 estimators. Simulations show that, in the presence of a high proportion of related individuals in a  
524 sample,  $r$  estimates should be treated with caution because they depend on the actual genetic

525 structure and allele frequencies of the sample as well as on relatedness estimators. However, when  
526 most individuals are unrelated, the problem is minor and can be ignored as a good approximation.  
527 In practice, random sampling from a large outbred population is expected to produce a sample  
528 containing only a small fraction of highly related individuals (e.g. Csillery *et al.*, 2006). However,  
529 for some species, family members (especially juveniles) tend to cluster spatially and sampling  
530 without realising and accounting for this family structure may lead to a sample containing just a few  
531 large families, as exemplified for a brown trout population (Hansen *et al.*, 1997).

532 It is tempting to estimate  $r$  and allele frequencies jointly to solve the 2<sup>nd</sup> problem. However,  
533 a proper account of the genetic structure in a sample in estimating allele frequencies requires a full  
534 pedigree of all individuals in the sample, not just the pairwise relatedness (Boehnke, 1991; Ritland,  
535 1996). For a sample of individuals with some simple genetic structures such as a 2-generation  
536 pedigree, it proves to be possible and effective to estimate both relationship and allele frequencies  
537 iteratively (Wang, 2004). Algorithms have also been developed to estimate allele frequencies and  
538 inbreeding jointly, assuming unrelated individuals within a population (Hill *et al.*, 1995) or a  
539 subpopulation (Gao *et al.*, 2007). However, no accurate method is available that allows for the joint  
540 estimation of pairwise relatedness and allele frequencies from the same sample. As a rough  
541 approximation, one may take a 3-step approach. First,  $r$  is calculated using crude allele frequencies  
542 estimated by assuming all individuals in a sample are unrelated. Second, a group of sampled  
543 individuals that are mutually unrelated or lowly related are identified using the crude  $r$  estimates,  
544 and is used for refining allele frequencies. Third, the refined allele frequencies are then used for  
545 calculating  $r$ . There are however several difficulties with this approach. First,  $r$  is a continuous  
546 quantity and it is unclear which threshold value should be used in selecting “unrelated” or “lowly  
547 related” individuals. Second, it can be difficult in practice to choose sufficiently many mutually  
548 unrelated individuals for accurate estimates of allele frequencies. Due to genuine genealogical  
549 relationships or merely sampling errors, the crude  $r$  estimates may indicate that individual  $X_1$  is  
550 related to  $X_2$ ,  $X_2$  to  $X_3$ , ...,  $X_{n-1}$  to  $X_n$ , while the other pairs of the  $n$  individuals may be unrelated as  
551 indicated by the  $r$  estimates. In such a case, one has to discard  $n-1$  individuals in calculating allele  
552 frequencies, which may become very inaccurate because of a small sample size when  $n$  is large.  
553 Third, simply discarding related individuals throws away information for allele frequencies.

554 Another problem caused by the practice of using the current sample as reference is the  
555 sampling errors of allele frequencies due to a finite sample size. Using the same individuals for  
556 estimating relatedness and allele frequencies introduces a negative covariance between them  
557 (Ritland, 1996). Effectively, the relatedness between two individuals is estimated by using the  
558 sample, including the two individuals, as reference. As a result, relatedness is underestimated by an

559 amount in the order of  $1/N$ , where  $N$  is the sample size. This bias can be removed by excluding the  
560 focal individuals in calculating allele frequencies used in estimating their relatedness (Queller &  
561 Goodnight, 1989; Ritland, 1996). However, the frequency of an allele present only in the focal  
562 individuals will be estimated to be zero by this exclusion procedure, which causes some estimators  
563 to become undefined.

564         Understanding the concepts of relatedness and inbreeding, especially their relative nature  
565 defined by the reference, is pivotal in correctly interpreting and applying the estimates in practice.  
566 First, relatedness and inbreeding should be understood as correlations between gametes between  
567 and within individuals caused by *recent* coancestry (coalescent). Essentially any two organisms are  
568 related and any individual is inbred on the earth because of the existence of recent or remote  
569 common ancestors. However, the relevant time scale for relatedness and inbreeding is the recent  
570 past (i.e.  $\ll 1/u$  generations where  $u$  is the mutation rate). This relatively short time scale was not  
571 explicitly spelt out by Wright (1921, 1922), but is necessary for relatedness and inbreeding to be  
572 useful in most practical applications. For example, an individual with inbreeding coefficient  $F$  is  
573 expected to be homozygous for an allele with frequency  $p$  (in the reference) at a probability of  $pF +$   
574  $p^2(1 - F)$ . This function applies when mutations are unimportant relative to drift and inbreeding,  
575 implying the most distant reference should be much smaller than  $1/u$ . Otherwise, mutations have to  
576 be accounted for in this probability. In practice, the time scale is invariably much shorter than  $1/u$ ,  
577 no matter in pedigree or marker based analyses. Within this time scale, how many generations as a  
578 minimum should we trace back for relatedness and inbreeding estimation? Obviously, the further  
579 the genealogy is traced back into the past, the higher the  $r$  and  $F$  estimates for all individuals in the  
580 current generation. However, for most applications, it is the relative values of  $r$  and  $F$  of the current  
581 focal individuals that are important. So long as the variance of  $r$  and  $F$  estimates becomes constant,  
582 then there is no need to trace pedigree further back. For a population with a mating system that  
583 allows well mixing of the genes (i.e. random mating), it is necessary to trace just  $\sim 5$  ancestral  
584 generations (e.g. Balloux *et al.*, 2004) to obtain genealogical  $F$  and  $r$  values that correlate highly  
585 with estimates obtained from a much deeper pedigree. This is understandable because a more  
586 remote ancestor will tend to contribute more evenly to all current descendants (Wray & Thompson,  
587 1990), and thus has smaller effect on the variance of  $r$  and  $F$ . However, for a population with a  
588 mating system that does not allow quick and extensive mixing of genes, such as subdivision with  
589 little migration, then a deeper pedigree with many more ancestral generations might be needed to  
590 provide a reliable description of the relative levels of inbreeding and relatedness. For example, Toro  
591 *et al.* (2002) showed that genealogical  $r$  estimates from a shallow pedigree of 5 generations are less  
592 correlated with molecular  $r$  estimates than those from a deep pedigree of 19~20 generations,

593 because the 62 pigs in the analysis were taken from two stains that were isolated. Assuming non-  
594 inbred and unrelated founders in a shallow pedigree may lead to distorted  $r$  and  $F$  estimates when  
595 the assumption is violated.

596 Second, it is the relative values of  $r$  and  $F$  that are relevant in most applications. For  
597 example,  $r$  and  $F$  estimates from pedigree or marker analyses are usually correlated with or  
598 regressed to a phenotype of a fitness component in investigations of inbreeding depression (Nielson  
599 *et al.*, 2012; Brekke *et al.*, 2010) and of a quantitative trait in estimating its heritability (Ritland,  
600 2000). The estimates are also compared between groups of individuals, such as between sexes or  
601 age classes, in studying the social and population structures. For example, Surridge *et al.* (1999)  
602 found that the average relatedness is negative between males and is positive between females in a  
603 European wild rabbit population, and interpreted the result as indicating male biased migration  
604 among social groups and female philopatry. In conservation management of endangered species,  $r$   
605 and  $F$  estimates can be used to optimise the selection and mating scheme for maximising the genetic  
606 diversity (e.g. Fernández *et al.*, 2003). In all these applications, the magnitude of  $r$  and  $F$  values is  
607 irrelevant, and a linear transformation of the estimates (by adding or multiplying a constant non-  
608 zero value) does not affect a downstream analysis. This means that, in a pedigree-based analysis,  
609 any reference generation suffices so long as the pedigree is sufficiently deep and thus variation of  $r$   
610 and  $F$  is close to its maximum. In a marker based analysis, allele frequencies at any reference  
611 generation can be used in  $r$  and  $F$  estimation if the estimators conform to the correlation definitions.

612 Third, caution must be exercised in applications in which the magnitudes of  $r$  and  $F$  values  
613 have more definite biological meanings. One such application is to classify pairs of individuals into  
614 well-separated relationship categories such as first- and second-degree relationships (e.g. Blouin *et al.*  
615 *et al.*, 1996; Glaubitz *et al.*, 2003; van Dan *et al.*, 2008) from pairwise relatedness estimates. If a dyad  
616 has an estimated  $r$  of 0.52 and 0.28, for example, it is classified as first (e.g. parent-offspring, full-  
617 sib) and second (e.g. half-sib, avuncular) degree relationship, respectively. However, the  
618 misclassification rate is generally very high even many markers are used (Blouin *et al.*, 1996;  
619 Glaubitz *et al.*, 2003; van Dan *et al.*, 2008; Csillery *et al.*, 2006), because of the high sampling  
620 variance of  $r$  and thus the wide overlap in distributions of possible  $r$  values between even well-  
621 separated relationships. This study shows further that the magnitudes of  $r$  values are more or less  
622 arbitrary, depending on the reference allele frequencies. When the current sample is used as  
623 reference,  $r$  is usually underestimated such that the average value of  $r$  for the sample is zero. These  
624 biases depend on the actual fine genetic structure of the sample, and the markers being used (Figure  
625 4). A better approach is to estimate relationships directly from marker data with a pairwise (e.g.  
626 Marshall *et al.*, 1998; Goodnight & Queller, 1999) or full (e.g. Wang & Santure, 2009) likelihood

627 method. This direct approach is much more robust to misspecifications of reference allele  
628 frequencies, and has the option to jointly estimate relationship and allele frequencies.

629 In this study, I investigated a few  $F$  and  $r$  estimators that are developed from population  
630 genetics models. When the underlying assumptions are met, they provide unbiased and marker-  
631 independent estimates of  $F$  and  $r$ . It is noticeable that some marker-based surrogate statistics are  
632 also proposed and applied in indicating the levels of inbreeding and relatedness. These include, for  
633 example, multilocus heterozygosity (MLH) or its complement for indicating inbreeding (e.g.  
634 Hansson & Westerberg, 2002) and similarity indexes (including the one used in (7)) (e.g. Ellegren,  
635 1999) for indicating relatedness. Compared with model-based estimators, these non-model based  
636 measurements may have a similar correlation coefficient with genealogical  $F$  and  $r$  estimates in  
637 some circumstances (Wang, 2011). However, these surrogate statistics are undesirable in several  
638 aspects. First, they do not estimate, although correlate with,  $F$  and  $r$ , and as a result have limited  
639 uses in practice. For example, MLH or its complement calculated from a set of markers as a  
640 surrogate for  $F$  cannot be used directly in predicting the probability of a genotype or the  
641 heterozygosity at another locus with given allele frequencies. Second, they are highly marker  
642 dependent. For the same individual, MLH is always higher for highly (e.g. microsatellites) than  
643 lowly (e.g. SNPs) polymorphic markers. For the same two individuals, similarity indexes and  
644 molecular coancestry are always lower for highly (e.g. microsatellites) than lowly (e.g. SNPs)  
645 polymorphic markers. This causes problems in comparing estimates involving individuals with  
646 missing data at different loci. An individual with data missing at highly polymorphic loci will tend  
647 to have a lower MLH, and higher similarity indexes and molecular coancestry with another  
648 individual, than an individual with no missing data or with missing data at lowly polymorphic loci.  
649 This marker-dependency also causes difficulties in comparisons within and across studies. Third,  
650 being empirical statistics lacking an underlying population genetics model, they have difficulty in  
651 weighing information among loci. In contrast,  $F$  and  $r$  estimators can weigh the information from  
652 different loci properly, using for example the inverse of the expected sampling variance of a locus  
653 (e.g. Ritland, 1996; Lynch & Ritland, 1999). The weighting becomes important when markers vary  
654 substantially in polymorphism. In view of these shortcomings, these surrogate statistics should be  
655 discouraged in practical applications.

656

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## 662 **References**

- 663 Anderson, A.D. & Weir, B.S. 2007. A maximum likelihood method for estimation of pairwise  
664 relatedness in structured populations. *Genetics* **176**: 421–440.
- 665 Boehnke, M. 1991. Allele frequency estimation from data on relatives. *Am. J. Hum. Genet.* **48**: 22-  
666 25.
- 667 Bonin, A., Bellemain, E., Bronken Eidesen, P., Pompanon, F., Brochmann, C. & Taberlet, P. 2004.  
668 How to track and assess genotyping errors in population genetics studies. *Mol. Ecol.* **13**: 3261-  
669 3273.
- 670 Brekke, P., Bennett, P.M., Wang, J., Pettorelli, N. & Ewen, J.G. 2010. Sensitive males: inbreeding  
671 depression in an endangered bird. *Proc. R Soc. Lond. B Biol. Sci.* **277**: 3677-3684.
- 672 Csillery, K., Johnson, T., Beraldi, D., Clutton-Brock, T., Coltman, D. *et al.* 2006 .Performance of  
673 marker-based relatedness estimators in natural populations of outbred vertebrates. *Genetics* **173**:  
674 2091–2101.
- 675 Ellegren, H. 1999. Inbreeding and relatedness in Scandinavian grey wolves *Canis lupus*. *Hereditas*  
676 **130**: 230–244.
- 677 Emik, L.O. & Terrill, C.R. 1949. Systematic procedures for calculating inbreeding coefficients. *J.*  
678 *Hered.* **40**: 51-55.
- 679 Fernández, J., Toro, M.A. & Caballero, A. 2003. Fixed contributions designs versus minimization  
680 of global coancestry to control inbreeding in small populations. *Genetics* **165**: 885 – 894.
- 681 Gao, H., Williamson S. & Bustamante, C.D. 2007. A Markov chain Monte Carlo approach for joint  
682 inference of population structure and inbreeding rates from multilocus genotype data. *Genetics*  
683 **176**: 1635–1651.
- 684 Goodnight, K. & Queller, D. 1999. Computer software for performing likelihood tests of pedigree  
685 relationship using genetic markers. *Mol. Ecol.* **8**: 1231–1234.
- 686 Grafen, A. 1985. A geometric view of relatedness. *Oxford Surv. Evol. Biol.* **2**: 28–89.
- 687 Hansen, M.M., Nielsen, E.E. & Mensberg, K.L. 1997. The problem of sampling families rather than  
688 populations: relatedness among individuals in samples of juvenile brown trout *Salmo trutta L.*  
689 *Mol. Ecol.* **6**: 469–474.
- 690 Hansson, B. & Westerberg, L. 2002. On the correlation between heterozygosity and fitness in  
691 natural populations. *Mol. Ecol.* **11**: 2467–2474.
- 692 Hardy, O.J. & Vekemans, X. 1999. Isolation by distance in a continuous population: reconciliation  
693 between spatial autocorrelation and population genetics models. *Heredity* **83**: 145–154.
- 694 Harris, D.L. 1964. Genotypic covariances between inbred relatives. *Genetics* **50**: 1319-1348.



695 Hill, W.G., Babiker, H.A., Ranford-Cartwright, L.C. & Walliker, D. 1995. Estimation of inbreeding  
696 coefficients from genotypic data on multiple alleles, and application to estimation of clonality in  
697 malaria parasites. *Genet. Res.* **65**: 53–61.

698 Jacquard, A. 1972. Genetic information given by a relative. *Biometrics* **28**: 1101-1114.

699 Jacquard, A. 1974. *The Genetics Structure of Populations*. Springer, New York.

700 Konovalov, D.A. & Heg, D. 2008. A maximum-likelihood relatedness estimator allowing for  
701 negative relatedness values. *Mol. Ecol. Res.* **8**: 256–263.

702 Lynch, M. & Ritland, K. 1999. Estimation of pairwise relatedness with molecular markers. *Genetics*  
703 **152**: 1753–1766.

704 Malecot, G. 1948. *Les mathematiques de l'heredite*. Masson et Cie, Paris, 63 pp.

705 Marshall, T., Slate, J., Kruuk, L. & Pemberton, J. 1998. Statistical confidence for likelihood-based  
706 paternity inference in natural populations. *Mol. Ecol.* **7**: 639–655.

707 Maynard Smith, J. 1998. *Evolutionary Genetics*. 2nd edn. Oxford University Press: Oxford.

708 Milligan, B. G., 2003. Maximum-likelihood estimation of relatedness. *Genetics* **163**: 1153–1167.

709 Nielsen, J.F., English, S., Goodall-Copestake, W.P., Wang, J., Walling, C.A., Bateman, A.W., *et al.*  
710 2012. Inbreeding and inbreeding depression of early life traits in a cooperative mammal. *Mol.*  
711 *Ecol.* **21**: 2788-2804.

712 Powell, J.E., Visscher, P.M. & Goddard, M.E. 2010. Reconciling the analysis of IBD and IBS in  
713 complex trait studies. *Nat. Rev. Genet.* **11**: 800–805.

714 Queller, D. C. & Goodnight, K. F. 1989. Estimating relatedness using molecular markers. *Evolution*  
715 **43**: 258–275.

716 Ritland, K. 1996. Estimators for pairwise relatedness and inbreeding coefficients. *Genet. Res.* **67**:  
717 175–186.

718 Ritland, K. 2003. Marker-inferred relatedness as a tool for detecting heritability in nature. *Mol. Ecol.*  
719 **9**: 1195–1204.

720 Rousset, F. 2002. Inbreeding and relatedness coefficients: what do they measure? *Heredity* **88**: 371–  
721 380.

722 Seger, J. 1981. Kinship and covariance. *J. Theoret. Biol.* **91**: 191-213.

723 Surridge, A.K., Ibrahim, K.M., Bell, D.J., Webb, N.J., Rico, C. & Hewitt, G.M. 1999. Fine-scale  
724 genetic structuring in a natural population of European wild rabbits (*Oryctolagus cuniculus*).  
725 *Mol. Ecol.* **8**: 299-307.

726 Thomas, S.C. 2010. A simplified estimator of two and four gene relationship coefficients. *Mol. Ecol.*  
727 *Res.* **10**: 986-994.

728 Toro, M., Barragán, C., Óvilo, C., Rodríguez, J., Rodríguez, C. & Silió, L. 2002. Estimation of  
729 coancestry in Iberian pigs using molecular markers. *Conserv. Genet.* **3**: 309–320.

730 van Horn, R., Altmann, J. & Alberts, S. 2008. Can't get there from here: inferring kinship from  
731 pairwise genetic relatedness. *Anim. Behav.* **75**: 1173–1180.

732 Van de Castele, T., Galbusera, P. & Matthysen, E. 2001. A comparison of microsatellite-based  
733 pairwise relatedness estimators. *Mol. Ecol.* **10**: 1539–1549.

734 Wang, J. 2002. An estimator for pairwise relatedness using molecular markers. *Genetics* **160**: 1203–  
735 1215.

736 Wang, J. 2007. Triadic IBD coefficients and applications to estimating pairwise relatedness. *Genet.*  
737 *Res.* **89**: 135–153.

738 Wang, J. & Santure, A.W. 2009. Parentage and sibship inference from multilocus genotype data  
739 under polygamy. *Genetics* **181**: 1579–1594.

740 Wang, J. 2011. Unbiased relatedness estimation in structured populations. *Genetics* **187**: 887–901

741 Wright, S. 1921. Systems of mating. *Genetics* **6**: 111–178.

742 Wright, S. 1922. Coefficients of inbreeding and relationship. *American Naturalist* **56**: 330–338.

743 Wright, S. 1965. The interpretation of population structure by *F*-statistics with special regard to  
744 systems of mating. *Evolution* **19**: 395–420.

745 Yip, S. P. 2002. Sequence variation at the human ABO locus. *Annals of Human Genetics* **66**: 1–27.

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**Table 1** Genotypes and frequencies of a large half-sib family

Shared parent			Half-sib offspring			Offspring sample allele frequency, $\hat{p}_x$
Genotype	Allelic state	Frequency	Genotype	Allelic state	Frequency	
$ii$	$\forall i$	$p_i^2$	$ix$	$\forall i, \forall x$	$p_x$	$\frac{1}{2}(\delta_{ix} + p_x)$
$ij$	$\forall i, \forall j \neq i$	$2p_i p_j$	$\{ix, jx\}$	$\forall i, \forall j \neq i, \forall x$	$\{\frac{1}{2}p_x, \frac{1}{2}p_x\}$	$\frac{1}{4}(\delta_{ix} + \delta_{jx}) + \frac{1}{2}p_x$